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Integrated Analysis of EIS, DCIR, and SoH for Degradation Diagnosis and Durability Assessment of NCM811 Lithium-Ion Batteries

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Abstract

Accurate battery state estimation is essential for electric-vehicle battery management systems (BMSs), directly improving their safety, durability, and operational reliability. This study proposes an integrated degradation-diagnosis framework that is, to our knowledge, among the first to combine electrochemical impedance spectroscopy (EIS), direct-current internal resistance (DCIR), and state of health (SoH) within a single, quantitative, low-complexity analysis of a hybrid-vehicle NCM811 lithium-ion battery module. Cycling-test data measured at 0, 400, 800, and 1200 cycles were reanalyzed using power-law regression, end-of-life (EOL) extrapolation, and cross-metric correlation analysis; the dataset was then extended to 2000 cycles (six checkpoints in total) to test the reliability of long-term lifetime prediction. Three findings are experimentally demonstrated. First, the ohmic resistance remained essentially constant during cycling, whereas the interfacial resistance increased by +422.7%, identifying interfacial (not bulk) resistance growth as the dominant degradation pathway. Second, power-law models substantially outperformed conventional exponential models for RE, DCIR, and SoH ($R^2 = 0.998, 0.999$, and 0.990 , respectively, vs. $R^2 = 0.870$ for the exponential SoH model); extending the dataset from four to six checkpoints narrowed the resulting EOL model-form uncertainty from a 3.5-fold to a 1.6-fold discrepancy (2776 vs. 9831 cycles, narrowing to 3124 vs. 4908 cycles). Third, a strong linear relationship between DCIR and SoH ($R^2 = 0.956$) was obtained, indicating that resistance-only monitoring can approximate SoH without full impedance measurement. Beyond these demonstrated results, the proposed framework offers potential value for SoH estimation, battery condition diagnosis, and state-estimation algorithm development in advanced BMSs; these broader applications have not been experimentally validated in this study and are discussed as directions for future work.



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Keywords: lithium-ion battery; electrochemical impedance spectroscopy; DCIR; state of health; model-form uncertainty

1. Introduction

The rapid growth of electric vehicles (EVs) and hybrid electric vehicles (HEVs) has significantly increased the demand for lithium-ion batteries with high energy density, long cycle life, and high operational reliability [1]. However, lithium-ion batteries inevitably experience capacity fade and internal resistance growth during repeated charge–discharge

cycling, leading to reduced driving range, degraded power capability, and potential safety concerns [2]. Consequently, accurate degradation analysis and reliable state-of-health (SoH) estimation have become essential functions of battery management systems (BMSs) [3].

Conventional battery health assessment has primarily relied on capacity retention and direct-current internal resistance (DCIR) [4]. Capacity retention is a representative indicator of battery aging; however, it generally requires full charge–discharge tests, limiting its applicability to real-time monitoring [5]. DCIR can be measured more conveniently and has therefore been widely adopted in practical BMS applications, but DCIR alone cannot adequately explain the electrochemical degradation mechanisms occurring within the battery [6]. As a result, degradation assessment based solely on capacity or DCIR provides limited insight into the evolution of internal electrochemical reactions [7].

Electrochemical impedance spectroscopy (EIS) has recently attracted considerable attention as an effective diagnostic technique for battery degradation because it enables the separation of ohmic resistance, interfacial resistance, charge-transfer resistance, and lithium-ion diffusion characteristics [8]. In particular, the growth of interfacial impedance associated with solid-electrolyte-interphase (SEI) formation is highly sensitive to early-stage degradation and therefore holds significant potential for battery health diagnosis and lifetime prediction [9]. However, previous studies have generally investigated EIS, DCIR, or SoH independently, and relatively few have integrated these degradation indicators into a unified framework for quantitative long-term degradation assessment [10]. Moreover, long-term lifetime predictions in the existing literature are typically reported from a single assumed degradation model, without examining how sensitive such predictions are to the choice of model. This forms an issue that becomes particularly important when only a limited number of early-cycle data points are available [11].

To address these limitations, this study proposes an integrated degradation analysis framework combining EIS, DCIR, and SoH using cycling data obtained from a hybrid-vehicle NCM811 lithium-ion battery module [12,13]. Rather than pursuing an experimentally complex, mechanistically exhaustive characterization of every possible degradation pathway, the proposed framework deliberately adopts a simple, practically oriented analytical approach based on a minimal set of readily obtainable cycling indicators and compact, low-parameter models, so that the resulting diagnostic insight remains directly applicable using data and equipment already available in standard battery-cycling and BMS-monitoring environments [14]. Power-law regression was employed to characterize the nonlinear degradation behavior of RE and DCIR, while exponential and power-law models were compared for long-term SoH degradation and end-of-life (EOL) prediction [15]; the original 0–1200-cycle dataset was further extended to 2000 cycles to quantify how the resulting EOL predictions depend on the assumed model form and to test whether denser cycling data reduces this dependence. Correlation analysis among RE, DCIR, and SoH was also performed to evaluate the feasibility of estimating battery health using resistance-based degradation indicators [16].

Prior studies have applied electrical equivalent-circuit (EEC/ECM) fitting to electrochemical impedance spectra, enabling automated SoH estimation with 5–10% accuracy for cells in intermediate and advanced degradation stages [17]. Distribution of Relaxation Times (DRT) analysis has also been used to deconvolve electrochemical impedance into timescale-resolved peaks, allowing overlapping processes such as SEI formation and charge transfer to be distinguished when conventional circuit fitting alone cannot separate them [18]. Separately, an integrated multi-indicator framework combining SOH, DCIR, and temperature/voltage deviation with a deep-learning classifier improved battery grading accuracy by 18% and reduced testing time by 30% compared with rule-based methods [19]. Building on this body of work, the present study instead adopts a deliberately simple,

geometric feature-extraction and regression-based framework (Section 2), trading mechanistic completeness for practical applicability, reproducibility, and explicit quantification of long-term prediction uncertainty, a dimension not addressed in the cited frameworks in Table 1.

Table 1. Brief comparison of representative prior frameworks and the present study.

Research	Analysis Elements
EEC/ECM fitting [17]	Automated EIS-based SoH diagnosis
DRT analysis [18]	Deconvolve overlapping impedance processes
Multi-indicator DL framework [19]	SOH + DCIR + ΔT + ΔV grading via deep learning
This study	Integrated EIS + DCIR + SoH regression framework

The main contributions of this study are summarized as follows. First, an integrated degradation analysis framework combining EIS and DCIR is proposed to complement conventional capacity-based battery health assessment, using a deliberately simple set of models chosen for practical applicability rather than mechanistic completeness. Second, the nonlinear degradation behaviors of RE and DCIR are quantitatively modeled using power-law regression with excellent fitting performance. Third, by comparing competing degradation models before and after extending the cycling range from 1200 to 2000 cycles, this study provides direct, quantitative evidence of model-form uncertainty in long-term EOL prediction and demonstrates how it can be reduced through additional cycling data. Fourth, the strong correlation between DCIR and SoH demonstrates the feasibility of resistance-based battery health estimation without full impedance measurement. Finally, the proposed framework provides a practical foundation for battery durability assessment, SoH-based condition diagnosis, and state-estimation algorithm development for advanced battery management systems.

2. Materials and Methods

The experimentally demonstrated degradation behavior of lithium-ion batteries remains incompletely characterized when EIS, DCIR, and SoH are analyzed independently, as in most prior single-indicator studies (Section 1). The objective of this study is therefore to integrate these three indicators within one quantitative framework and to test how sensitive the resulting long-term lifetime predictions are to the assumed degradation-model form. This objective is met without resorting to experimentally complex, mechanistically exhaustive characterization. Instead, this study deliberately adopts a simple, practically oriented analytical approach [20]. It relies on a minimal set of readily obtainable cycling-test indicators (RE, IM, DCIR Degradation%, and SoH) and compact, low-parameter mathematical models (power-law and exponential degradation models, and linear cross-metric regression) to identify the dominant, practically actionable causes of battery lifetime degradation, rather than pursuing a fully resolved electrochemical mechanistic picture. This approach is intentionally chosen over more elaborate but experimentally demanding techniques such as dense-frequency equivalent-circuit fitting, post-mortem material characterization, or physics-based electrochemical simulation because it enables rapid, low-cost degradation diagnosis using data and equipment already available in standard battery-cycling and BMS-monitoring environments.

2.1. Experimental Data Basis and Test Setup

The RE, IM, DCIR Degradation%, and SoH values reanalyzed in this study originate from a controlled cycling test of a hybrid-vehicle lithium-ion battery module (six NCM811-based cells connected in series; nominal fully charged module voltage, 25.2 V;

extracted from a 300 V hybrid-vehicle system). Testing was performed on a single battery pack ($n = 1$), consistent with [20]. As seen in Figure 1, the module was cycled at a 1C rate between a fully charged state and a minimum module voltage of 18.0 V, inside an ISO 12405-compliant, temperature-controlled chamber maintained at 20 °C. Impedance (RE, IM) was obtained by electrochemical impedance spectroscopy, and DCIR was computed from the voltage response to a constant applied current; SoH was evaluated from capacity retention corrected for internal-resistance growth [21], specifically $\text{SoH} = (C_{\text{current}}/C_{\text{rated}}) \times 100$, with an internal-resistance-corrected form, $\text{SoH} = (C_{\text{current}}/C_{\text{rated}}) \cdot (R_0 - V_{t0})/R_{\text{current}} \times 100$, following the original experimental study on which this reanalysis is based.

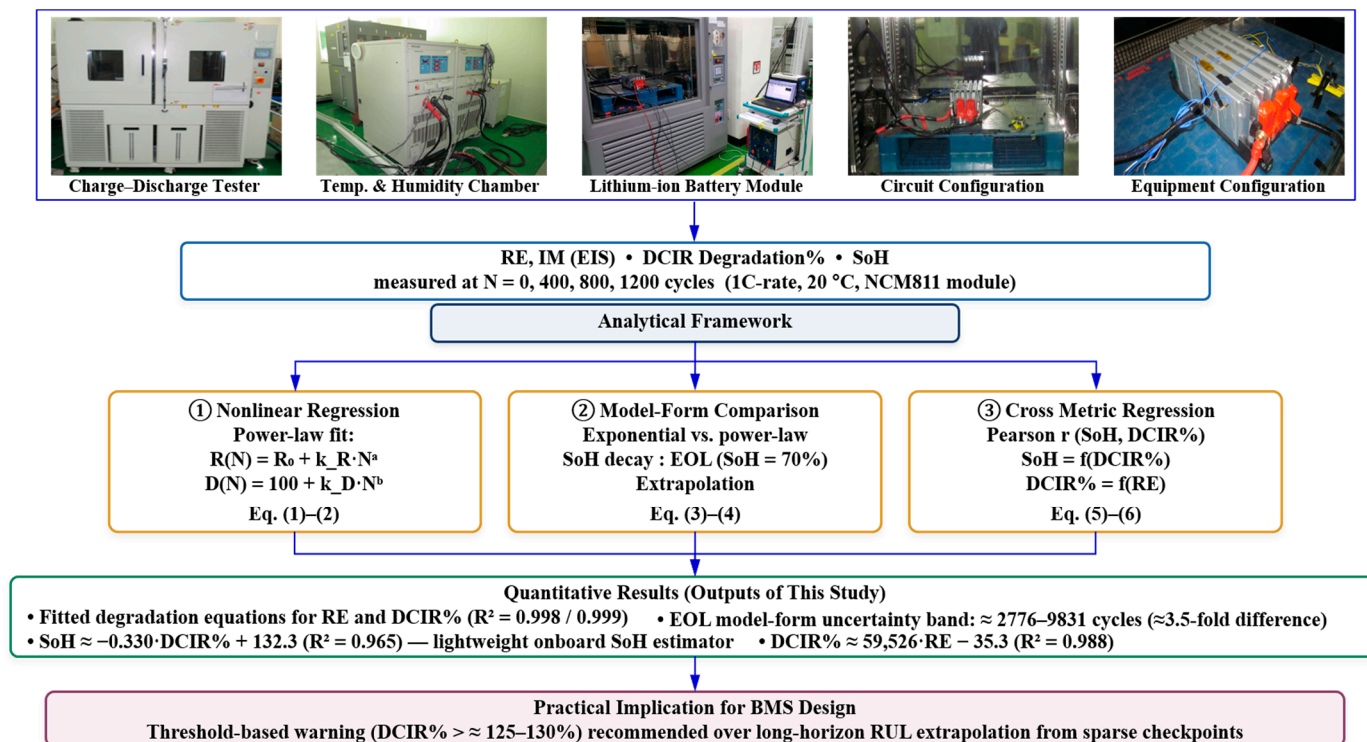


Figure 1. Analytical framework of this study and its practical implication for BMS design.

The instrument-level settings for EIS (frequency range, AC excitation amplitude, instrument model) and the precise DCIR pulse protocol (pulse-current magnitude, duration, and ΔV measurement timing) were not recorded beyond what is reported in [20] and are therefore not available for inclusion here.

The original cycling test comprised four checkpoints: 0 (Standard), 400, 800, and 1200 cycles at which full EIS Nyquist spectra, DCIR, and SoH were all measured. A preliminary model-comparison analysis based on these four checkpoints, however, revealed substantial model-form uncertainty in long-term lifetime prediction: candidate exponential and power-law degradation models, although both fitting the 0–1200-cycle data reasonably well, diverged by more than a factor of three when extrapolated to the conventional end-of-life (EOL) criterion of $\text{SoH} = 70\%$ (≈ 2776 cycles versus ≈ 9831 cycles, respectively). Because this divergence could not be resolved from four checkpoints alone, additional cycling was performed under identical test conditions and equipment to extend the DCIR and SoH dataset to 2000 cycles, yielding two further checkpoints at 1600 and 2000 cycles and a total of six checkpoints (0, 400, 800, 1200, 1600, and 2000 cycles) for DCIR and SoH. Full EIS Nyquist spectra were not re-acquired at 1600 and 2000 cycles; consequently, the impedance decomposition presented in Section 3.1 (R_s , interfacial resistance, IM peak, and Warburg slope; Table 5) is reported for the original 0–1200-cycle range, whereas the SoH

degradation-model comparison in Section 3.4 and the cross-metric regression in Section 3.5 draw on the extended 0–2000-cycle, six-checkpoint dataset. This extension was undertaken specifically to improve the statistical reliability of long-term degradation-model selection and EOL prediction, not to characterize additional degradation mechanisms beyond those already resolved at 1200 cycles.

Because the present contribution is primarily analytical, the additional cycling performed to reach 2000 cycles followed the same protocol, equipment, and measurement procedures as the original 0 to 1200 cycle test, and no new measurement technique was introduced. Previously and newly measured summary values were used together as fixed inputs to independent nonlinear-regression and correlation analyses not previously applied to this dataset.

During cycling, real-time voltage and current signals were monitored through a LabVIEW-based data acquisition (DAQ) system, which was specifically configured to capture fast transient responses throughout the charge–discharge process. Given the inherent risk of thermal runaway or explosion associated with lithium-ion battery testing, the experimental setup was further equipped with a purpose-built ventilation system to maintain operational safety. Representative voltage and current traces obtained under the 1C-rate cycling protocol are shown in Figure 2. This protocol was configured to emulate constant-current (CC) fast-charging behavior typical of real-world electric-vehicle usage, whereby charging was halted as soon as the module reached full-charge voltage, with the cycle proceeding directly into discharge. Under these realistic operating conditions, the measured charging duration fell short of the theoretically expected 1 h CC charging time by roughly 10 min, and the delivered charge capacity was correspondingly lower than the theoretical value. Accordingly, all cycling experiments and subsequent analyses in this work were grounded in these empirically observed operating conditions rather than in idealized theoretical charging assumptions.

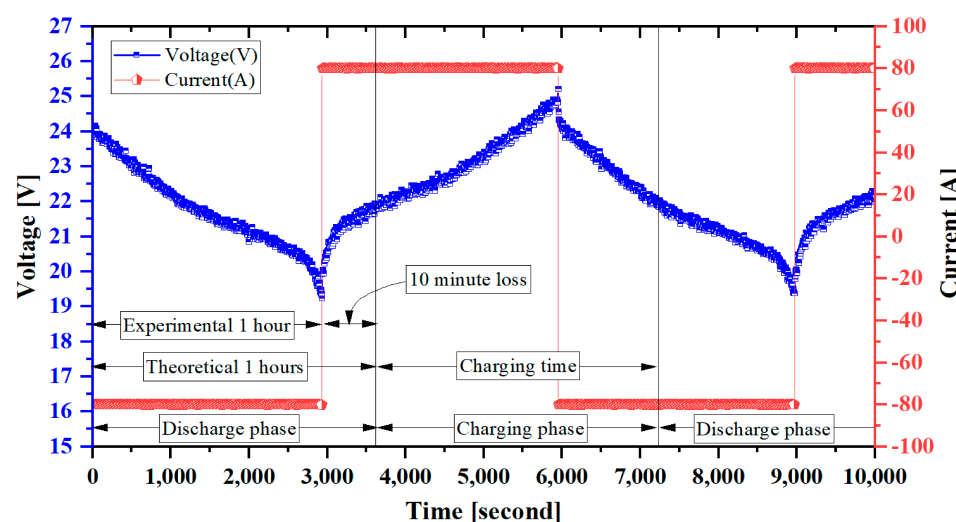


Figure 2. Representative voltage/current-vs-time waveform.

The charge–discharge tester used in this study was designed to evaluate the performance and degradation characteristics of lithium-ion batteries through repetitive cycling under controlled operating conditions. The detailed specifications of the charge–discharge tester are summarized in Table 2, and the operating conditions of the temperature–humidity chamber are presented in Table 3. The test specimen was a commercially available NCM811 lithium-ion battery module extracted from a hybrid electric vehicle, cycled under the conditions summarized in Table 4. All experiments were performed under identical conditions to ensure the reproducibility and reliability of the experimental results.

Table 2. Specifications of the charge–discharge test system.

Items	Specification
Operating Type	Charge/Discharge/OCV/DC-Imp/Pattern/Cycle Repetition
Voltage Range	10 V–450 V
Voltage Setting Accuracy	±0.1% (Full Scale)
Voltage Measurement Accuracy	±0.1% (Full Scale)
Current Range	0~±150 A
Current Setting Accuracy	±0.1% (Full Scale)
Current Measurement Accuracy	±0.1% (Full Scale)
Operation Mode	Independent operation by channel
Input Power	AC 220 V, 3-Phase

Table 3. Operating conditions of the EV battery environmental chamber.

Items	Specification
Standard Compliance	ISO 12405-1, ISO 12405-2, GB/T 3
Internal Dimensions (mm)	3000 (W) × 1800 (D) × 800 (D)
Heating Control Method	Electric Power Supply System
Temperature Accuracy (Full Range)	±0.5 °C

Table 4. Experimental conditions for battery lifetime evaluation.

Items	Specific Conditions
Category	Specification
Battery Type	Lithium-ion battery pack
Cell Configuration	6 cells connected in series
Nominal Voltage per Cell	4.2 VDC (fully charged)
Fully Charged Pack Voltage	25.2 VDC
Minimum Discharge Voltage (Pack)	18.0 VDC
Current Control	1C rate
Ambient Temperature	20 °C (maintained constant)
Total Test Cycles	1200 cycles (original test); extended to 2000 cycles for DCIR and SoH monitoring (see Section 2.1)
Measured Variables	Voltage, current, temperature, capacity retention, internal resistance, etc.

2.2. Power-Law Degradation Model for RE and DCIR Degradation%

Resistance-based degradation metrics were modeled with a two-parameter power-law form referenced to cycle number $R(N)$ [22]:

$$R(N) = R_0 + k_r \cdot N^\alpha \quad (1)$$

where R_0 is the initial (asymptotic) resistance, k_r is a rate coefficient, and α is a degradation exponent governing curvature. The same functional form, with an additive baseline of 100%, was applied to DCIR Degradation% [23]:

$$D(N) = 100 + k_D \cdot N^\beta \quad (2)$$

Parameters (R_0, k_r, α) and (k_D, β) were estimated by nonlinear least-squares fitting (Levenberg–Marquardt) against the four reported checkpoints, and goodness of fit was assessed with the coefficient of determination R^2 [24]. R^2 was used as the primary criterion for selecting between the exponential and power-law model forms, consistent with standard practice for comparing regression models of comparable parameter count.

2.3. Competing SoH Decay Models and End-of-Life Extrapolation

Two structurally different candidate models were fitted to the SoH trajectory to test the sensitivity of long-horizon extrapolation to the assumed functional form. The first is an exponential-decay model, motivated by first-order capacity-fade kinetics [25]:

$$\text{SoH}(N) = 100 \cdot e^{-kN} \quad (3)$$

The second is a power-law decay model, structurally consistent with the RE and DCIR Degradation% fits in Equations (1) and (2):

$$\text{SoH}(N) = 100 - k_s \cdot N^\gamma \quad (4)$$

Both models were fitted to the same four checkpoints, and each was extrapolated forward in cycle number to identify the cycle count at which SoH first reaches the conventional end-of-life threshold of 70%. Because the two models are fitted to identical data yet embody different assumptions about degradation curvature, the divergence between their EOL predictions provides a direct, quantitative estimate of model-form uncertainty information not available from either model in isolation.

2.4. Resistance Based SoH Estimation

The statistical relationship between SoH and DCIR Degradation% was quantified using the Pearson correlation coefficient r , computed over the six-checkpoint dataset (0–2000 cycles). Ordinary least-squares linear regression was used to derive two transferable empirical equations [26]:

$$\text{SoH} \approx a_1 \cdot \text{DCIR}\% + b_1 \quad (5)$$

$$\text{DCIR}\% \approx a_2 \cdot \text{RE} + b_2 \quad (6)$$

Equation (5) was fitted over the full six-checkpoint range (0–2000 cycles), for which DCIR% and SoH were both measured. Equation (6) was fitted over the original four checkpoints (0–1200 cycles), for which full EIS-based RE measurements were available [27–29]. These regressions test whether a resistance-only measurement (DCIR or RE) can approximate SoH without a full EIS-based RE/IM measurement, which is of practical interest for embedded BMS applications with limited sensing hardware.

3. Research Results

3.1. Experimental Data Validation for Battery RE and IM

Figure 3 shows the EIS Nyquist spectra of the battery measured under the Standard, 400-cycle, 800-cycle, and 1200-cycle conditions, annotated to highlight four physically distinct regions: (i) a high-frequency inductive loop; (ii) the ohmic resistance (R_s), corresponding to the high-frequency real-axis intercept; (iii) an interfacial semicircle in the medium-frequency region, reflecting solid-electrolyte-interphase (SEI) and charge-transfer processes; and (iv) a Warburg diffusion tail in the low-frequency region, representing lithium-ion diffusion behavior [20].

The analysis indicates that the high-frequency R_s remains nearly unchanged under all cycling conditions, suggesting that the resistance associated with bulk conduction paths including the electrolyte, separator, and current collector undergoes only negligible variation during cycling. In contrast, the diameter of the interfacial semicircle in the medium-frequency region increases progressively with cycle number, with a more pronounced enlargement observed after 800 cycles, indicating that repeated cycling promotes SEI-layer growth and increased charge-transfer resistance. The Warburg diffusion tail exhibits a nearly identical slope across all cycling conditions, indicating that lithium-ion diffusion characteristics remain relatively stable throughout cycling. Battery degradation is therefore

considered to be governed primarily by the growth of interfacial reaction resistance rather than by an increase in diffusion resistance or bulk ohmic resistance.

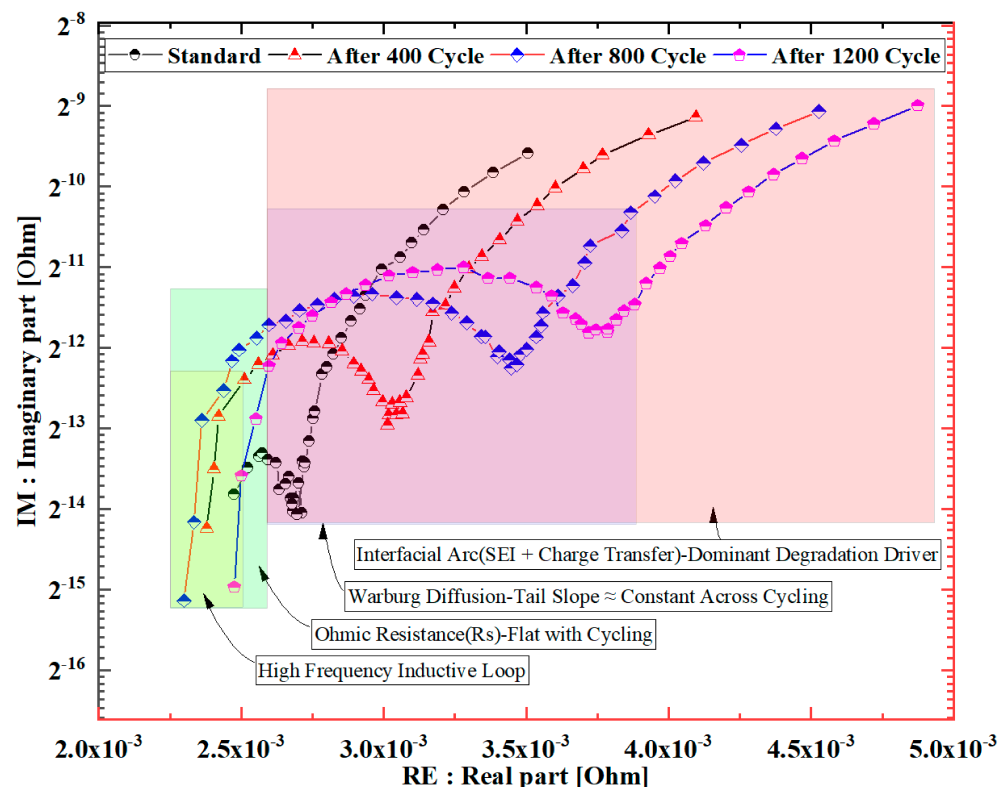


Figure 3. Four physically distinct regions.

These findings offer a perspective on battery degradation distinct from conventional evaluation based on capacity retention or DCIR alone: the diameter of the interfacial semicircle responds sensitively even during early-stage degradation, indicating strong potential as an early degradation indicator for remaining-useful-life (RUL) prediction.

Figure 4 illustrates the evolution of R_s and interfacial resistance as a function of cycle number. R_s remains nearly constant within approximately 2.3–2.5 m Ω , whereas interfacial resistance increases continuously, with a more pronounced increase observed after 800 cycles. This confirms that battery performance deterioration is dominated by the growth of interfacial impedance rather than by changes in bulk ohmic resistance.

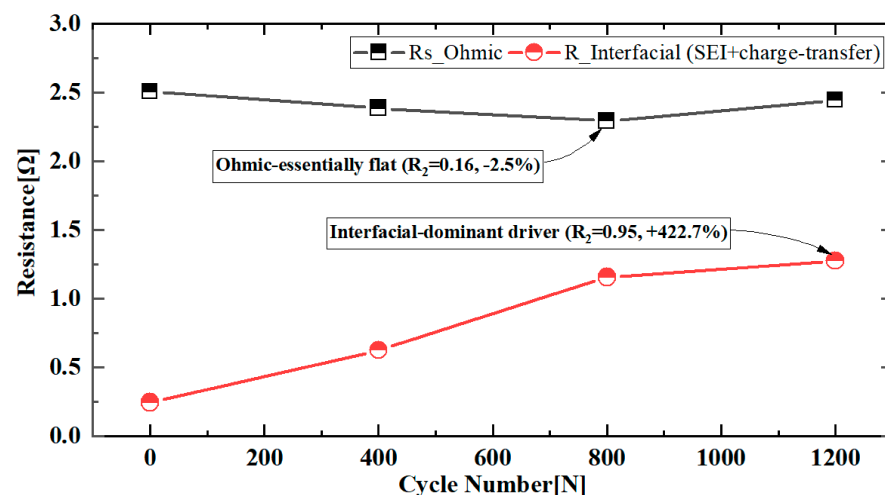


Figure 4. Evolution of ohmic resistance (R_s) and interfacial resistance (SEI + charge-transfer) with cycle number, 0–1200 cycles.

Table 5 summarizes the evolution of the key impedance features. While R_s remained nearly constant throughout cycling, both $R_{\text{interfacial}}$ and IM_{peak} increased continuously, confirming that interfacial degradation is the dominant contributor to overall impedance growth, whereas the near-constant Warburg slope indicates stable lithium-ion diffusion characteristics over this cycle range.

Table 5. Decomposed impedance features across cycling (extracted from full Nyquist spectra).

Condition	R_s Ohmic (m Ω)	$R_{\text{interfacial}}$ (m Ω)	IM_{peak} (m Ω)	Warburg Slope
Standard	2.51	0.24	0.13	1.58
400 Cycle	2.39	0.62	0.26	1.65
800 Cycle	2.29	1.16	0.39	1.63
1200 Cycle	2.44	1.28	0.49	1.61

3.2. Power-Law Fit of RE Degradation

Figure 5 illustrates the evolution of RE as a function of cycle number together with the power-law fitting results (Equation (1)). The experimental RE increases continuously with cycle number, from approximately $2.30 \times 10^{-3} \Omega$ in the initial state to approximately $2.93 \times 10^{-3} \Omega$ after 1200 cycles. The fitted model closely follows the experimental data over the entire range, achieving $R^2 = 0.998$ (Table 6).

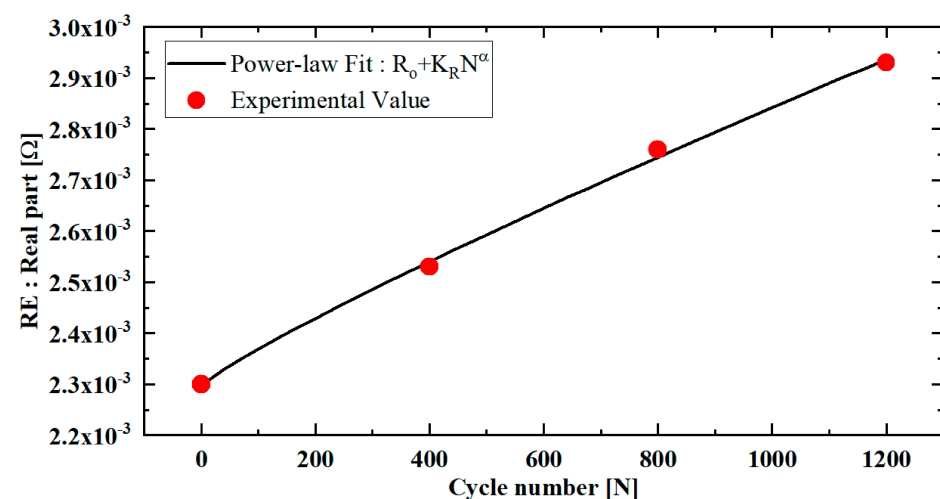


Figure 5. Power-law fit of RE degradation against the four reported checkpoints (0–1200 cycles).

Table 6. Fitted power-law parameters for RE and DCIR Degradation% (0–1200 cycles).

Metric	Model	Fitted Parameters	R^2
RE (Ω)	$R(N) = R_0 + k_r N^a$	$R_0 = 2.298 \times 10^{-3}$, $k_r = 1.226 \times 10^{-6}$, $\alpha = 0.882$	0.998
DCIR Degradation (%)	$D(N) = 100 + k_D N^b$	$k_D = 0.304$, $\beta = 0.682$	0.999

The continuous increase in RE is consistent with the interfacial impedance growth observed in the Nyquist plots (Section 3.1), suggesting progressive SEI growth and increasing charge-transfer resistance during repeated cycling. The high goodness of fit indicates that the power-law model captures the underlying degradation behavior rather than providing a merely numerical curve fit, supporting its use in combination with conventional DCIR and capacity-retention indicators for battery health assessment and RUL prediction.

3.3. Power-Law Fit of DCIR Degradation%

Figure 6 presents DCIR Degradation% as a function of cycle number together with the power-law fitting results (Equation (2), Table 4). DCIR Degradation% increases continuously and nonlinearly with cycle number, and the fitted model accurately reproduces the experimental trend over the entire 0–1200-cycle range ($R^2 = 0.999$), indicating that DCIR is an effective indicator for characterizing internal-resistance-related battery degradation.

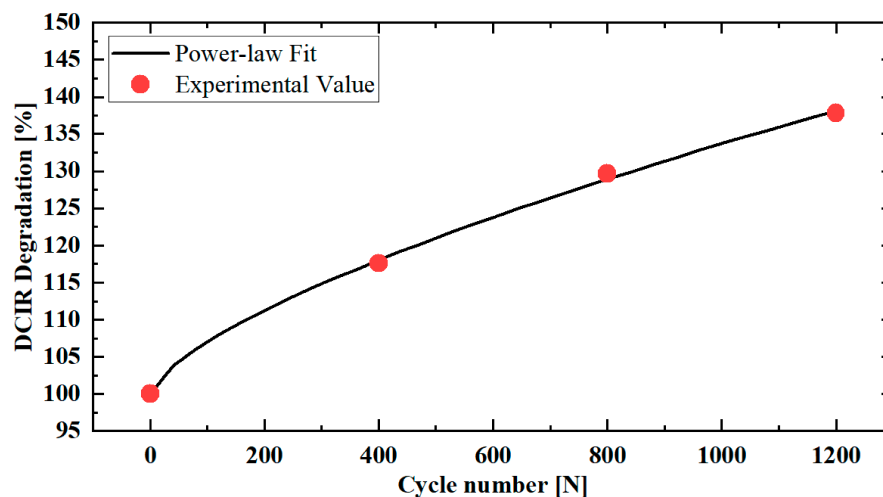


Figure 6. Power-law fit of DCIR Degradation% against the four reported checkpoints (0–1200 cycles).

3.4. Model-Form Sensitivity of SoH Extrapolation and End-of-Life Prediction

Figure 7 presents the variation in SoH with cycle number, based on the six experimentally measured checkpoints Standard (0), 400, 800, 1200, 1600, and 2000 cycles—together with the EOL predictions obtained from the exponential (Equation (3)) and power-law (Equation (4)) models fitted to these data. The x-axis represents cycle number N under the constant 1C-rate, 20 °C protocol; the y-axis represents SoH (%), where 100% denotes the pristine state and 70% denotes the EOL threshold conventionally adopted in the automotive battery industry.

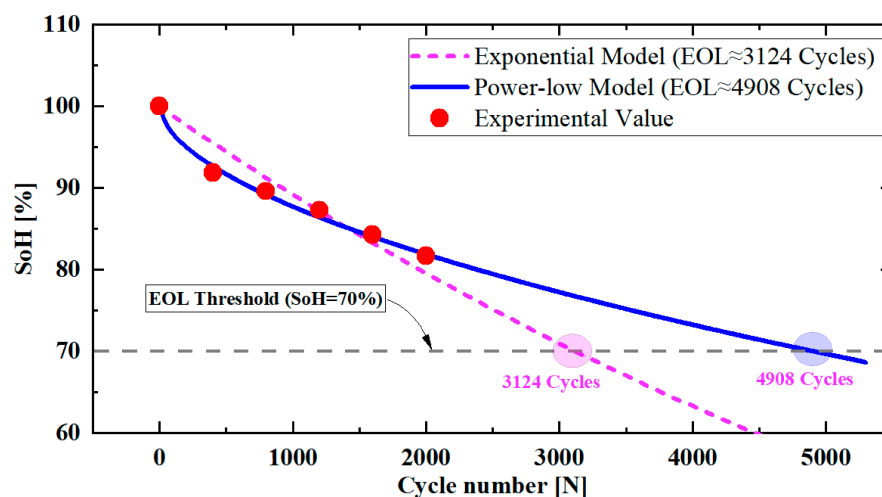


Figure 7. Model-form sensitivity of EOL extrapolation: exponential vs. power-law SoH decay models, fitted to the six-checkpoint (0–2000-cycle) dataset.

The exponential model predicts an EOL of approximately 3124 cycles, whereas the power-law model predicts approximately 4908 cycles, a 1.6-fold (57%) discrepancy despite both models being fitted to the identical dataset. This divergence arises solely from the assumed mathematical functional form, not from measurement error or material vari-

ability. The power-law model ($R^2 = 0.990$) substantially outperforms the exponential model ($R^2 = 0.870$), indicating that the actual degradation behavior follows a nonlinear, decelerating pattern rather than constant-rate exponential decay. Extending the measured checkpoints from four (0–1200 cycles) to six (0–2000 cycles) narrowed the discrepancy between the two models' EOL predictions from a 3.5-fold difference (2776 vs. 9831 cycles) to a 1.6-fold difference (3124 vs. 4908 cycles in Table 7), demonstrating that increasing the density of measured cycling data reduces model-selection uncertainty.

Table 7. Comparison of competing SoH decay models and their EOL extrapolations (0–2000 cycles).

Model	Fitted Parameters	R^2 (0–2000 Cycles)	Extrapolated EOL Cycle (SoH = 70%)
Exponential: $100 \cdot e^{-kN}$	$k = 1.142 \times 10^{-4}$	0.870	≈ 3124
Power-law: $100 - k_s N^\gamma$	$k_s = 0.253, \gamma = 0.562$	0.990	≈ 4908

This degradation pattern, observed in a hybrid-vehicle cell employing an NCM811-based cathode and a graphite/silicon composite anode, is consistent with the impedance decomposition in Section 3.1. The relatively rapid SoH decline between 400 and 800 cycles corresponds to the early-stage regime dominated by active SEI film formation, providing a physical rationale for why the power-law model's sub-linear exponent ($\gamma = 0.562$, i.e., $\gamma < 1$) reproduces the data more accurately than the exponential model. The deceleration in SoH decline beyond 1200 cycles further suggests that interfacial resistance growth enters a relatively stabilized regime, consistent with degradation being governed predominantly by interfacial rather than ohmic resistance.

Beyond the specific material system examined here, this analysis illustrates a general point for battery-lifetime-prediction research conducted under similarly limited early-cycle data: reporting a single deterministic EOL value can be statistically misleading, whereas fitting multiple candidate models and reporting their divergence as an explicit uncertainty band constitutes a more robust validation procedure. Whether this specific procedure generalizes quantitatively to other battery chemistries and operating conditions was not tested in this study and remains a direction for future validation (see Section 4).

3.5. Cross-Metric Correlation and Regression Analysis

SoH and DCIR Degradation% were strongly and negatively correlated across the six-checkpoint dataset (Pearson $r = -0.978$), confirming a statistically robust inverse relationship. Ordinary least-squares regression of SoH on DCIR Degradation% (Equation (5)) yielded:

$$\text{SoH} \approx -0.258 \cdot \text{DCIR\%} + 123.8 \quad (R^2 = 0.956) \quad (7)$$

As seen in Figure 8, a second regression linking DCIR Degradation% to RE (Equation (6)), fitted over the original four checkpoints for which full EIS-based RE was available, yielded:

$$\text{DCIR\%} \approx 59,526 \cdot \text{RE} - 35.3 \quad (R^2 = 0.988) \quad (8)$$

Equation (7) is valid within the observed measurement range (DCIR Degradation% ≈ 100 –168%) and Equation (8) within $\text{RE} \approx 0.0023$ – $0.0029 \, \Omega$; neither should be extrapolated beyond these ranges without re-validation against additional cycle data. Because DCIR-based measurement is considerably simpler to implement onboard a vehicle than full EIS, Equation (7) suggests that an approximate SoH estimate can be obtained from DCIR monitoring alone within the validated range, supporting a tiered BMS-monitoring strategy in which lightweight DCIR-based estimation is used for continuous onboard tracking while periodic EIS measurement is reserved for higher-fidelity recalibration.

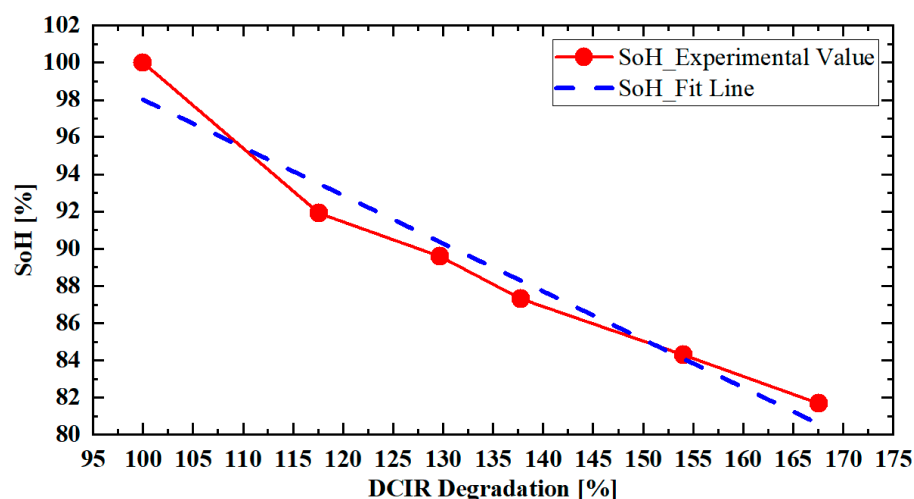


Figure 8. Empirical linear regression of SoH against DCIR Degradation%, fitted to the six-checkpoint (0–2000-cycle) dataset (Equation (5)).

4. Discussion

The degradation behavior was investigated through EIS and DCIR analyses. R_s remained nearly constant throughout cycling, whereas interfacial resistance and IM_{peak} increased continuously, with only a minor change in the Warburg slope. This indicates that degradation is governed primarily by SEI growth and increased charge-transfer resistance rather than by bulk ohmic resistance.

The power-law model consistently outperformed the conventional exponential model across the RE, DCIR, and SoH datasets. Extending the dataset from four to six checkpoints narrowed the model-form uncertainty in EOL prediction from a 3.5-fold to a 1.6-fold discrepancy, confirming that denser cycling data improves prediction reliability.

Overall, the proposed EIS- and DCIR-based analysis offers a quantitative framework for battery durability assessment beyond conventional capacity-based evaluation, with potential to support SoH estimation and condition diagnosis in BMS applications. Within the tested module and operating conditions, the observed reduction in model-form uncertainty further suggests a practical criterion for determining how much additional cycling data is needed before a long-term lifetime prediction can be considered reliable; whether this criterion holds for other battery chemistries and operating conditions remains to be validated.

Several limitations should be acknowledged. This study is based on a single hybrid-vehicle battery module tested under a single set of operating conditions (1C rate, 20 °C, one SOC window, NCM811 chemistry). Battery-to-battery variability was not assessed, and the effects of temperature, C-rate, and SOC window on the reported degradation kinetics, fitted parameters, and EOL predictions were not examined. Consequently, the applicability of the proposed framework demonstrated here is limited to the tested module, chemistry, and operating conditions; extension to other chemistries (e.g., LFP, NCA), multi-cell/multi-module populations, or different temperature and C-rate regimes should be regarded as a proposed direction for future validation rather than an established result of the present study.

5. Conclusions

This study investigated the long-term degradation behavior of lithium-ion batteries using EIS, DCIR, and SoH analyses, extending the original 1200-cycle dataset to 2000 cycles to improve the reliability of long-term lifetime prediction. The following conclusions were obtained:

- (1) EIS analysis revealed that the ohmic resistance (R_s) remained nearly constant throughout cycling (2.3–2.5 m Ω), whereas the interfacial resistance and IM_peak increased continuously (+422.7% and +267.2% from Standard to 1200 cycles, respectively), indicating that degradation is primarily governed by SEI growth and increased charge-transfer resistance rather than by changes in bulk ohmic resistance.
- (2) Both RE and DCIR Degradation% exhibited nonlinear, sub-linear power-law increases with cycle number ($R^2 = 0.998$ and 0.999 , respectively); the power-law model also represented SoH degradation more accurately than the conventional exponential model ($R^2 = 0.990$ vs. 0.870).
- (3) Extending the dataset from four to six checkpoints narrowed the model-form uncertainty in EOL prediction from a 3.5-fold discrepancy (2776 vs. 9831 cycles) to a 1.6-fold discrepancy (3124 vs. 4908 cycles), indicating that denser cycling data materially improves prediction reliability and should be reported as an explicit uncertainty band rather than a single deterministic estimate.
- (4) A strong correlation was observed between DCIR and SoH ($r = -0.978$, $R^2 = 0.956$), yielding an empirical linear equation ($\text{SoH} \approx -0.258 \cdot \text{DCIR\%} + 123.8$) that enables lightweight SoH estimation from resistance-only monitoring within the validated range.
- (5) The proposed EIS- and DCIR-based degradation analysis complements conventional capacity-based evaluation and, within the tested module, chemistry, and operating conditions, provides a practical basis for battery durability assessment and SoH-based condition diagnosis. Because this study examined a single module under a single set of conditions (Section 4), future work should validate the proposed methodology including formal equivalent-circuit fitting and testing across multiple modules, chemistries, C-rates, temperatures, and SOC windows before its applicability to advanced BMS state-estimation algorithms can be considered general.

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